Time-Window Sequential Analysis: An Introduction for Pediatric Psychologists

Jill MacLaren Chorney,[1,2] PhD, Abbe Marrs Garcia,[3,4] PhD, Kristoffer S. Berlin,[5] PhD, Roger Bakeman,[6] PhD, and Zeev N. Kain,[7,8] PhD

[1]*Department of Anesthesiology, Dalhousie University,* [2]*Division of Pediatric Anaesthesia and Centre for Pediatric Pain Research, IWK Health Centre,* [3]*Department of Psychiatry and Human Behavior, Brown Medical School,* [4]*Division of Child and Family Psychiatry, Rhode Island Hospital,* [5]*Department of Psychology, Ohio University,* [6]*Department of Psychology, Georgia State University,* [7]*Department of Anesthesiology and Perioperative Care, University of California, Irvine, and* [8]*Department of Pediatrics, Children's Hospital of Orange County, University of California, Irvine*

All correspondence concerning this article should be addressed to Jill Chorney, PhD, Centre for Pediatric Pain Research, 8th Floor (South), IWK Health Centre, 5850/5980 University Ave, PO Box 9700, Halifax, Nova Scotia, B3K 6R8, Canada. E-mail: jill.chorney@dal.ca

Received June 24, 2009; revisions received February 23, 2010; accepted March 3, 2010

Objective Pediatric psychologists are often interested in interactions among individuals (e.g., doctors and patients, parents and children). Most research examining the nature of these interactions has used correlational analyses. Sequential analysis provides greater detail on contingencies during interactions and the way that interactions play out over time. The purpose of this article is to offer a non-technical introduction to sequential analyses for pediatric psychologists. **Methods** A more recent derivation of the basic method, called time-window sequential analysis, is introduced and distinguished from other forms of sequential analysis. **Results** A step-by-step pediatric psychology example of time-window sequential analysis is provided and the integration of sequential analysis with traditional statistical methods is discussed. An example of physician–child interaction during anesthesia induction is used to illustrate the technique. **Conclusion** Sequential analysis is a technique that is useful to pediatric psychologists who are interested in contingencies among data collected over time.

Key words methodology; sequential analysis.

Sequential analytic techniques provide pediatric psychologists with a tool to answer a host of questions about interactions among children, parents, medical personnel, and others. Are adolescents more likely to disclose risk behaviors in a clinic setting following physician empathic statements than they are at other times in the interaction with the physician? Are children's statements about pain more likely to occur after parent states maturity demands than after other types of parent statements? Are children with feeding difficulties more likely to put non-preferred foods in their mouth following direct neutral request from parent than following other parent behaviors? Each question is relevant to pediatric psychologists and each also has the potential for the examination of sequential associations among behaviors of interest.

The technology and methods for conducting sequential analyses have evolved over time, and the purpose of this article is to offer a non-technical introduction to sequential analyses for pediatric psychologists. Specifically this article will provide an introduction to a recent derivation of the basic method, called time-window sequential analysis. Time-window sequential analysis will be distinguished from other forms of sequential analysis and a step-by-step pediatric psychology-relevant example will be provided.

Journal of Pediatric Psychology 35(10) pp. 1061–1070, 2010
doi:10.1093/jpepsy/jsq022
Advance Access publication April 14, 2010

It should be acknowledged that methods other than sequential analysis might illuminate interpersonal interactions. For example, frequency counts of specified behaviors could be examined using the appropriate type of correlational analyses (Karazsia & van Dulmen, 2009) or changes in mean levels of specified behaviors could be compared pre- and post-intervention. Correlational and mean-level analyses are valuable methods in the pediatric psychologists' armamentarium of statistical techniques, but neither of them addresses the temporal contingency between particular adult and child behaviors, which is one of the key strengths of sequential analysis. Information about the contingencies that govern the behavior of children and adolescents with medical issues is a powerful tool and has clear implications for shaping interventions with these youth, families, and others involved in their lives and care.

Overview of Sequential Data Coding and Analytic Techniques

The term sequential analysis generally refers to a group of techniques that identify patterns of behaviors and examine contingencies among data collected over time (Bakeman & Gottman, 1997). Although different sequential analytic techniques have the same underlying analytic principles, it is conceptually helpful to differentiate the types of data and research questions that are appropriate for each technique.

Event sequential data coding

Event sequential data coding is the most simplified form of observational coding. In this type of data collection, behaviors of interest are coded from transcripts, videotapes, or audiotapes using a single set of codes that are *mutually exclusive* (i.e., only one code can be associated with a particular event) and *exhaustive* (i.e., there is some code for every behavior (Bakeman & Gottman, 1997; Bakeman & Quera, 1995, 2009). This type of coding results in a single *stream* (otherwise known as string or sequence) of codes. A hypothetical example of this type of data is shown in Figure 1a. In this example, physician reassurance, physician empathic touch (i.e., holding the child's hand), and child cry are the coded behaviors.

Event sequential coding has the strength of requiring little technology to collect, but strips information on timing of behaviors from the data thus making representations of behaviors that have meaningful durations (e.g., crying) problematic. For example, in Figure 1a, if the third event (child cry) lasted for 5 s and the sixth event (also child cry) lasted for 5 min, there is no distinction in how they are represented in event sequential data. Investigators have addressed this problem by inserting codes in the stream to denote that a duration-meaningful behavior continues to occur. In the case of Blount et al. (1989) this issue was resolved by inserting a code that represented ''cry'' in the coding log every three events while cry was ongoing. In this way, the duration of cry was roughly captured because cry was represented multiple times in the coding log. Unfortunately, this approach

(a)

Event	1	2	3	4	5	6	7	8	9	10
CODE:	Physician Empathic Touch	Physician Reassures	Child Cry	Physician Empathic Touch	Physician Reassures	Child Cry	Physician Reassures	Physician Empathic Touch	Physician Reassures	Child Cry

(b)

Time:	1:01	1:02	1:03	1:04	1:05	1:06	1:07	1:08	1:09	1:10	1:11	1:12	1:13
Physician Reassures	1	0	0	0	0	0	0	1	0	0	1	1	0
Physician Empathic Touch	1	1	1	1	0	0	1	1	1	1	1	1	0
Child Cry	0	0	1	1	1	1	1	0	1	1	1	1	1

Figure 1. Data representations corresponding to (**a**) event sequential data coding. Data are represented as a single mutually exclusive and exhaustive stream. No time information included. Note that two behaviors that begin simultaneously must be ordered, and ongoing behaviors (empathic touch and cry) are inserted every three codes while ongoing. (**b**) Timed-event sequential data coding. Data are represented as three mutually exclusive and exhaustive streams (0 = non-occurrence, 1 = occurrence). Note that physician reassurance is represented as a momentary event code and physician empathic touch and child cry are represented as state codes.

misses important information on timing of gaps between behaviors and behavior discontinuation. This hypothetical example also highlights another limitation of event sequential coding—the inability to represent co-occurring behaviors. In event sequential data coding, behaviors that co-occur must be ordered so that they can be represented as successive codes in the single stream. Usually some decision rule is imposed to represent order (i.e., whichever speaker is loudest gets coded first), but this distinction is artificial and ordering depends on the acuity of transcribers. For example, in Figure 1a it is not clear whether the alternation of child cry and physician reassures (from event 5 to event 10) represents a true alternation between these behaviors, or whether it is an attempt to represent the ongoing co-occurrence of child cry and physician reassurance.

Analysis of Event Sequential Data

Lag sequential analysis is the specific sequential technique that is appropriate for event sequential data. Using this type of data, lag sequential methods ask whether the presence of one code (often termed the ''given'' code) increases the probability that another code (often termed the ''target'' code) will occur. The term *lag* denotes where in the sequence the given and target codes occur. For example, *Lag 1* is indicative of analyses examining the ''given'' code followed by the ''target'' code as the next event in the stream. In the case of the example in Figure 1, an event sequential question at Lag 1 would be ''Does physicians' use of reassurance (''given'' code) increase the probability that a child will cry (''target code'') *in the next behavior*?'' Lag 2 represents the target code as the second event after the given code and so on. The underlying assumption in these analyses is that behaviors have a relatively immediate contingent relation. There are obvious drawbacks to this assumption; theoretically we rarely expect the behavior of one individual to have an immediate and uninterrupted effect on the behavior of another individual. There are also practical limitations to this type of analyses. If researchers are interested in contingencies outside of codes that immediately precede or follow each other (e.g., codes at Lag 2 or greater), the complexity of these analyses become overwhelming. Readers interested in a recent and more detailed discussion of lag sequential analyses are referred to Connor, Fletcher, and Salmon (2009). It is notable that event-sequential data can be examined using windows (i.e., whether a ''target'' code is likely to occur within a window of five events from the ''given'' code), but this approach has not been widely used.

Timed-Event Sequential Data Coding

In contrast to simple event sequential coding, timed-event sequential coding captures information about timing and duration. When durations are important to an investigation, the onset and offset times of behavioral codes are recorded (these are often called duration or *state* codes). In other cases, durations may not be deemed as important as examining when a particular behavior began or durations may not be meaningful for a particular behavior. In these cases, onset times only are recorded (these are often called *momentary* codes).

Whereas an event sequential approach requires coders to force co-occurring behaviors into successive codes in a stream (Figure 1a), timed-event sequential data preserves information about co-occurrence by fitting codes into separate streams. For example, one could have one stream of codes about physician verbal reassurance. In this stream the physician is coded as either reassuring or not reassuring for each second in the observation. The physician reassurance stream could be coded concurrently with a second stream of codes about physician nonverbal behavior (e.g., coded as: empathically touching, medically touching, or not touching at all for each second in the observation) and a third stream about child crying (e.g., coded as either crying or not crying for each second in the observation). In this way, timed-event sequential data more accurately captures behaviors that naturally co-occur. Figure 1b is a code-time grid (Bakeman, 2009) representation of the timed-event coding of the same hypothetical data that was shown in Figure 1a. Coding using a timed-event approach has the disadvantage of being more difficult to collect by hand, but computer programs have been developed to facilitate this task (e.g., Noldus' The Observer XT, Mangold International's INTERACT). Coding behaviors into separate streams has the added benefit of allowing codes in different streams to be coded at a different time by a different coder.

Analysis of Timed-Event Sequential Data

Two time-relevant sequential techniques are appropriate for timed-event coded data. The first technique is similar to the event lag-sequential technique, but rather than asking questions about what occurs in the *next behavior*, time lag-sequential analysis asks about what occurs in the *next second* (if Lag 1 analysis is used). Using the same example question from procedural interactions, a time lag-sequential question would ask, ''Does the occurrence of adult reassurance increase the probability that a child will start to cry in the *next second*?'' For obvious reasons, this type of analysis is limited. Rarely do we expect contingencies to be played out in such a specific time frame.

The second time relevant technique, *time-window* sequential analysis, allows for more flexibility in underlying assumptions about contingencies (Bakeman, 2004; Bakeman, Deckner, & Quera, 2005; Yoder & Tapp, 2004). Time-window sequential analyses asks whether the presence of a particular behavior (i.e., a ''given'' code) increases the probability that another behavior (i.e., a ''target'' code) will occur within a specified temporal window. Using this technique, theoretically or empirically relevant time windows (e.g., within 2 s) can be set for analysis, thus setting the stage for research questions such as ''Does the occurrence of adult reassurance increase the probability that a child will start to cry *within a window of 3 s?*'' or ''Does the provision of a direct command increase the probability that a child will comply with a request within a window of 5 s?''.

We will not review each of the sequential methods described above in full detail, but instead will focus on time-window sequential analysis. It is our assertion that coding data using timed-event sequences and the corresponding use of time-window sequential analysis is a method that is relevant to multiple areas of pediatric psychology, but has not been widely used in this area. This type of data collection and analysis offers the most flexibility of the sequential analytic techniques and uses a data representation format that best captures how interactions unfold over time (i.e., has the most ecological validity). Readers interested in other types of sequential analytic strategies (traditional and multilevel approaches) are encouraged to read Bakeman and Gottman (1997), Gottman and Roy (1990), Howe, Dagne, and Brown (2005) and Stoolmiller and Synder (2006).

We make two assumptions before we continue further. First, we assume that the investigator using time-window sequential analysis is interested in exploring patterns of interactions among individuals (or within an individual) over time. Second, we assume that the investigator has familiarity with observational coding systems especially the importance of and methods for assessing interrater reliability. For in-depth coverage of these topics, the interested reader is referred to Bakeman and Gottman (1997; see also Bakeman, Quera, & Gnisci, 2009).

Time-Window Sequential Analysis: Perioperative Interactions as an Example

To demonstrate time-window analysis, we will use an example of data from the Behavioral Interaction-Perioperative Study (BIPS; reference blinded for review). BIPS is a large-scale observational study examining interactions among children, parents, and healthcare providers in the perioperative setting. Video recordings of anesthesia induction were collected from 292 children undergoing anesthesia induction by mask for outpatient elective surgeries. Behavior was coded using a version of the Perioperative Child–Adult Medical Procedure Interaction Scale (Caldwell-Andrews, Blount, Mayes, Kain, 2005) revised to facilitate timed-event coding. The coding scheme was applied using The Observer XT (Noldus Inc, The Netherlands) software. Data were exported from The Observer XT to text files, converted into SDIS-formatted data files (Bakeman & Quera, 2008), and compiled for analysis using the sequential analysis program, GSEQ Version 5.0 (Bakeman & Quera, 2009).

For the purposes of this example, two codes from the R-PCAMPIS will be used: (a) Medical reinterpretation by the anesthesiologist (reinterpreting medical equipment and procedures as non-threatening or medical play; for example: ''Look at the mountains'' referring to the anesthesia machine) and (b) Medical play by the child (verbal or nonverbal behavior indicating that the child is engaged in play with medical equipment; for example: pointing to the ''mountains'' on the monitor). In line with previous coding systems of patient-provider interactions (e.g., Roter Analysis Interaction Scale; Roter & Larson, 2002), these behaviors were treated as ''momentary'' event codes, that is only their onset times and not their offset times were recorded (Bakeman & Gottman, 1997). Codes were assigned to the smallest unit of speech that conveyed a complete thought and multiple thoughts in a row were coded as separate instances of the code. For example, ''look at the mountains...here, look at this'' was coded as two onsets of reinterpretation in close temporal succession.

We will not provide a detailed review of the literature on this topic, but do note that the relation between adult behavior and children's coping is not a new query in the pediatric procedural pain literature. Using event-sequential and correlational analyses, Blount and colleagues identified a constellation of adult behaviors that were related to children's coping during medical procedures (Blount et al., 1989). In the perioperative setting, Chorney et al. (2009)

showed that a similar constellation of adult behaviors (including medical reinterpretation) were correlated with children's coping (including medical play). As with any correlational analysis, however, it is impossible to draw causal conclusions from this data; we do not know whether adults affected children or vice versa (or whether some third variable accounts for these results). Time window-sequential analysis can provide more insight into this question. Although sequential analysis does not permit causal conclusions, it does provide us more information about the temporal contingency between these behaviors. We can determine if reinterpretation is likely to lead to play or if play is likely to lead to reinterpretation.

The First Steps in Time-Window Sequential Analysis: Asking Sequential Questions

As with other statistical methods, the utility of time-window sequential analysis depends on the researcher's ability to formulate relevant research questions and hypotheses. In the case of time-window analyses, research questions must include elements of contingency and time. In our example, we are interested in the relation between anesthesiologists' reinterpretation and children's medical play. The question ''What is the relation between medical reinterpretation and medical play?'' is a correlational question and not sufficiently detailed for examination with sequential analyses. To reframe this correlational question into one that is appropriate for sequential analysis, it is necessary to increase the level of specificity and include time information. For example, we could ask about the temporal contingency between anesthesiologist reinterpretation and children's medical play: *Are children more likely to be engaged in medical play within 4 s of an anesthesiologist medical reinterpretation than they are at other times*? This question suggests a potential play-cueing function of medical reinterpretation—that children are responding to anesthesiologists attempts to engage them in play. Alternatively, we can ask about the contingency in the opposite direction: *Are anesthesiologists more likely to use medical reinterpretation within 4 s after a child starts to engage in medical play they are at other times?* In this case we ask about the reinterpretation-cuing function of play—that anesthesiologists are responding to children. In both cases, these questions include a hypothesized contingent relation (e.g., medical reinterpretation as an antecedent and medical play as a consequence) and a specified time window (e.g., 4 s). It is notable that the length of the time window is somewhat arbitrary (e.g., 3 s vs. 5 s). Although there is some statistical guidance on this (Yoder & Tapp, 2004), the current recommendation is to use time window durations that make sense given the nature of the data. The rate at which behavior is occurring in the data, and in our case the rate at which the participants are interacting, was relevant in choosing a relatively short duration for this window. In a paradigm in which the rate of coded behavior is slower, longer window durations would make more sense.

Preparing Data for Time-Window Sequential Analysis: Recoding Data

To address our first research question—*Are children more likely to be engaged in medical play within 4 s of an anesthesiologist medical reinterpretation than they are at other times*?—we begin by defining an appropriate time window. Figure 2 provides an illustrative example of data. We define the second just after the anesthesiologist reinterprets as ''in'' the reinterpretation window along with the following 3 s. This 4-s window is illustrated in Figure 2. In this segment of data, the anesthesiologist used reinterpretation twice, once at 1:03 and once at 1:10 and the child showed play behavior three times at 1:05, 1:09, and 1:10 (here observations are coded into 1-s time intervals).

Time:	1:01	1:02	1:03	1:04	1:05	1:06	1:07	1:08	1:09	1:10	1:11	1:12	1:13
Physician Reinterprets	0	0	1	0	0	0	0	0	0	1	0	0	0
Child Plays	0	0	0	0	**1**	0	0	0	*1*	*1*	0	0	0

Figure 2. Timed-event data demonstrating defined window for time-window sequential analysis. Shading indicates window following physician reinterpreting. Bolded value indicates child play that occurs inside the physician reinterpret window. Italicized values indicate child play that occurs outside the physician reinterpret window.

Table I. *Observed and Expected Values Contingency Table: Target Behavior (Child Medical Play) and given Window (4 s Following Anesthesiologist Reinterpretation)*

	Medical play	No medical play	Total
Inside reinterpretation window:	4 (A)	59 (B)	63
Expected value:	1.45	61.55	
Outside reinterpretation window:	7 (C)	407 (D)	414
Expected value:	9.55	404.45	
Total	11	466	477

Note: Odds ratio = (A ÷ B)/(C ÷ D) = (A × D)/(B × C) = 3.94; Yules Q = (AD – BC)/(AD + BC) = .062.

Representing Sequential Data: The contingency table

Once data are recoded into time windows, a contingency table is constructed (Table I). This table tallies the occurrences and non-occurrences of our target code (i.e., child medical play) and specified window for the other code (i.e., the 4 s after anesthesiologist medical reinterpretation). For ease of presentation in this manuscript, cells (where the rows and columns meet) in the contingency table are labeled A, B, C, and D (as is conventional, e.g., see Yoder and Tapp, 2004) where: cell A represents the number of seconds in which the ''target'' code (i.e., began reinterpretation) occurred within the specified time window, cell B represents the number of seconds within the specified time window that did not also contain a ''target'' code, cell C represents the number of seconds in which the ''target'' code occurred outside the specified window, and cell D represents the number of seconds in which neither the ''target'' code nor the window code occurred. The contingency table for our first example, ''*Are children more likely to be engaged in medical play within 4 s of an anesthesiologist medical reinterpretation than they are at other times*?'' is shown in Table I. Note that we provide data from a single participant (4940) as an example throughout this section. The same process would be followed for each subject and summary statistics can be calculated for each subject. The use of summary statistics will be discussed later.

Statistics for Time-Window Sequential Analyses

Once contingency tables are generated, a range of statistics can be calculated to describe the distribution of the data and contingencies. Of particular interest is the odds ratio, a measure of the relation between two variables. In the case of time-window analysis, the odds ratio is an index of sequential association that accounts for the base rates of the antecedent given and consequent target (an important issue highlighted later in this section). Odds ratios are commonly used in epidemiology and biostatistics and have intuitive appeal as they can be interpreted as directly as how many times more (or less) likely one event is relative to another. Odds ratios have a lower bound of 0 and an upper bound of infinity with 1.0 indicating no association. In the context of sequential analysis, odds ratios above 1 indicate that a target event is more like to occur relative to a given event. An odds ratio less than 1 indicates that the target event is less likely to occur relative to a given event.

In our case, if the odds ratio is greater than 1, it means that the odds of an onset of child's medical play during the 4 s after anesthesiologist medical reinterpretation are greater than the odds of an onset occurring outside the window. The formula for the odds ratio is: OR = (A/B)/(C/D), which is definitional, or (A × D)/(B × C), which may be easier to compute; where A, B, C, and D refer to the cells in the contingency table described above (Table I; Durlak, 2009). Although the Odds Ratio is, in fact, itself an index of effect size, it can be algebraically transformed into another index of effect size, Yule's *Q*, a statistic that ranges from –1 to + 1, like the familiar Pearson product–moment correlation. The formula for Yule's *Q* is (AD – BC)/(AD + BC) or (OR – 1)/(OR + 1). In this example, although only 36.4% of medical plays occurred within the 4 s after anesthesiologist reinterprets, the odds of a medical play onset occurring within this window were 3.94 times greater than at other times (i.e., OR = 3.94, Yule's *Q* = .60).

This result seems counter intuitive. How can a child be more likely to play in this window when the majority of their play is outside this window? The answer is related to base rates; the more common two behaviors are, the more likely it is that they will follow each other by chance. Alternatively, the less frequent behaviors are the less common it will be for them to occur in close temporal proximity. In our data, given that there are relatively few occurrences of reinterpretation, when medical play occurs within these few opportunities, it is significant. Another way to think about this is by examining how often we would expect these behaviors to co-occur given their base-rates, and comparing this to what was observed in the data. The formula for calculating expected values is the standard one used for computing chi-square

(Bakeman & Gottman, 1997). Per this formula, the expected values are also provided in Table I.

As shown in Table I, if there was no relation between medical play and medical reinterpretation, we would expect to see 1.45 episodes of play within the window after reinterpretation. In our observed data, we see 4 play onsets in this window. Although these values (4 vs. 1.45) appear to be different, just as in traditional statistics, we are required to test the probability that this difference occurred simply by chance (i.e., for statistical significance). The z-test (or adjusted residual as it is termed in the log-linear literature; Haberman, 1978) will be familiar to many readers as a test of the difference between observed and expected values. As in traditional statistics, in the case of sequential analysis, the z-test is computed by dividing the difference between the observed and expected values by the standard deviation of this difference (Bakeman & Gottman, 1997; Yoder & Tapp, 2004). The standard deviation of the difference is a function of the expected sequential frequency and the simple probabilities of both behaviors (for exact formula, see Bakeman & Gottman, 1997, or Yoder & Tapp, 2004). In our case, the z-test of medical play beginning within the window of reinterpretation starts is 2.29, above the cutoff of 1.96 for a statistically significant finding with a p-value set at .05.

Making Sense of Sequential Results

So far, we have transformed a correlational question—What is the relation between anesthesiologist reinterpretation and child medical play?—into a sequential question—*Are children more likely to be engaged in medical play within 4 s of an anesthesiologist medical reinterpretation than they are at other times*? However, one sequential question may not provide the entire picture of the temporal relation between two behaviors. In our example above, we found that children were more likely (four times more likely in fact) to engage in medical play just following medical reinterpretation from an anesthesiologist than at any other time. Based solely on this result, we would be likely to conclude that anesthesiologist reinterpretation was serving a ''play-cuing'' function; but what about the other direction? As we discussed earlier, one way to address this question is by looking at reinterpretation following medical play. The approach is the same as that just described. To address our second research question—*Are anesthesiologists more likely to use medical reinterpretation within 4 s after a child starts to engage in medical play they are at other times?*—we define a window as the 4 s following a child medical play. The frequency counts (observed and expected) for the same example participant used above can be found in Table II. In Table II, the odds ratio is 2.36. Thus, this anesthesiologist is about twice as likely to reinterpret this child just after a child medically plays than at any other time. The Yule's Q is 0.40. The expected value for reinterpretation in the window just after medical play is 1.5, which does not significantly differ from the observed value of 3, z-score = 1.32, $p > .05$.

Table II. *Observed Values Contingency Table: Target Behavior (Anesthesiologist Reinterpret) and given Window (4 s Following Child Medical Play)*

	Reinterpret	No reinterpret	Total
Inside medical play window:	3	48	51
Expected value	1.5	49.5	
Outside medical play window:	11	415	426
Expected value	12.5	413.5	
Total	14	463	477

Note: Odds ratio = (A/B)/(C/D) = (A × D)/(B × C) = 2.36; Yules $Q = (AD - BC)/(AD + BC) = .040$.

The results of time-window sequential analysis from this sample participant better explicate the nature of the relation between the anesthesiologist and the child in this interaction. This child is almost four times more likely to engage in medical play following the anesthesiologist's attempt to engage (via reinterpretation) them compared to any other time. The adjusted residual of this comparison was significant, suggesting that this contingency is statistically meaningful. In contrast, this anesthesiologist is only two times more likely to attempt to engage this child following the child's use of medical play. This comparison was not statistically significant. Whereas correlational data would indicate only that these two behaviors are related, more detailed sequential analysis suggests that the anesthesiologist is driving this interaction. In this one case, although both were positive, the effect was stronger for the anesthesiologist-to-child than for the child-to-anesthesiologist effect.

So far we have shown how to conduct time-window sequential analyses for one case or participant. This is useful for single subject research studies, but these analyses are also useful in studies with more than one participant. Primarily, as we discuss in the next section, Yule's Qs can serve as outcome scores and be analyzed with standard statistical techniques. We can also calculate the mean and standard deviation of Yule's Qs across participants and use these values descriptively. In addition, if we have two groups and want to know simply if they differ, we could use a binomial or sign test. For example, if we had 30 cases and 21 or more of them showed a particular pattern (i.e., children more likely to engage following a reinterpretation than at any other time), we would say the deviation from the expected 15–15 split was significant, $p < .05$, per two-tailed sign test (Bakeman & Robinson, 2005).

Integrating Sequential Analyses with Other Statistical Methods

Now that we have presented an overview, we wish to note that an additional benefit of time window sequential analysis is that it can be integrated into other statistical approaches (e.g., correlation and regression, analysis of variance, structural equation modeling, latent growth curves). We may be interested in the relations between sequential results and traditional paper and pencil measures or demographic data and so ask, for example, *''Is a child more likely to engage in medical play following reinterpretation from Anesthesiologist A or B?''* or *''Is the child's age related to how likely they are to engage in medical play following anesthesiologists reinterpretation?''* Conceptually, these questions ask ''Does the strength of the specified association (i.e., effect size) between a reinterpretation and medical play vary according to the child's age or anesthesiologist identity.'' Note that these questions are specific to temporal relations; we ask whether a boy is more likely to engage in medical play following anesthesiologists' reinterpretation. This is a more specific question than simply asking whether a boy is more likely to engage in medical play than a girl.

In order to answer these particular questions the pediatric researcher can use the values of Yules's Q for *each participant* as dependent variables in subsequent analyses. The use of a program such as GSEQ, which computes summary contingency scores like Yule's Q for each participant, greatly facilitates this process. Note that Yule Q's and odds ratios can be calculated only for participants who have occurrences of both the given and the target behaviors; otherwise division by 0 would occur, resulting in an undefined (missing) value. In terms of the examples presented above, to determine if *children are more likely to respond to reinterpretation with medical play for anesthesiologist A and B,* we compare the mean Yule's Q for Anesthesiologist A to B using a simple t-test. In our data set we find that the mean Yule's Q for Anesthesiologist A is 0.13 ($n = 15$) and the mean Yule's Q for Anesthesiologist B is 0.47 ($n = 26$) with $t = 2.25$, $p < .05$, $d = .72$ Thus, it appears that Anesthesiologist B is more effective at engaging children than Anesthesiologist A. To answer our second question, *''Is the child's age related to how likely they are to engage in medical play following anesthesiologists reinterpretation?''* the bivarate correlation between the individually calculated Yule's Q and child age was determined. In our data set this correlation is small, $r(104) = .108$, $p > .05$, and not statistically significant. These are just two of an infinite number of ways to integrate sequential analyses with other statistical methods. The key is to treat a contingency index derived from sequential analysis as a score like any other—one that can be analyzed along with scores derived from other sources, using any of a variety of familiar statistical procedures. One caveat: as with any other kind of score analyzed with a group design, having a sufficient sample size to detect as statistically significant effects of a size you think important (i.e., power analysis) always needs to be considered.

Conclusions

Sequential techniques allow researchers to examine questions about the contingency between behaviors, which is not afforded by other statistical techniques. In the case of the example provided here, attending to temporal contingency provides important information about the nature of the relation between the behaviors of interest. This asset not withstanding, results from sequential analysis can be complex and sometimes challenging to interpret. Because the level of specificity in the analyses is so great, so too must be the level of specificity in the conclusions. This fact is often at odds with the desire to offer direct, unqualified conclusions from one's work (e.g., ''adult behavior promotes children's coping''). Rather, the conclusions that can be drawn from a set of sequential analyses provide a more detailed view of the transactional relationship among behaviors of interest. It is also notable that sequential analysis is subject to the same limitations and caution in interpretation as correlational analyses; we can not rule out the possibility that a third variable is responsible for the demonstrated relation. Despite these limitations, we believe that the increased accuracy from fine-grained level of analysis and specificity of the results can lead to very precise intervention strategies.

Although the example provided here is specific to children's coping during medical procedures, it is important to note that sequential analysis has utility across pediatric psychology domains. Researchers who are interested in interactions amoung parents and children, physicians and patients, or teachers and students will find this technique useful. Of particular value is the fact that sequential analysis can better contextualize correlational findings. Sequential approaches can query which participant in the interaction is the leader and which is the follower (i.e., which participant is more likely to cue the other). For example, in an interaction between and anxious child and their parent, is a request for support from the child more likely to prompt reassurance from their parent, or is reassurance more likely to prompt a child's request for support? Sequential approaches can also determine the efficacy of a specific behavior. For example, is a child more likely to eat a non-preferred food following a direct command or an indirect command? In this way, we gather more information about this interaction than is provided with simple correlation. It is our hope that this article has helped to demystify the process of conducting time-windowed sequential analyses and that we have convinced some readers to incorporate sequential techniques into their own research.

Acknowledgments

The authors wish to thank Lindsey Cohen, PhD, Marina Tolou-Shams, PhD, and Jack Nassau, PhD for their helpful comments on a previous version of this article.

Funding

National Institute of Child Health and Human Development (2R01HD037007-06 to Z.N.K.); National Institutes of Health.

Conflicts of interest: None declared.

References

Bakeman, R. (2004). Sequential analysis. In M. Lewis-Beck, A. E. Bryman, & T. F. Liao (Eds.), *The SAGE Encyclopedia of Social Science Research Methods*. Thousand Oaks, CA: SAGE Publications, Vol. 3, pp. 1024–1026.

Bakeman, R. (2009). Reflections on measuring behavior: time and the grid. In E. Tucker, M. Viswanathan, & G. Walford (Eds.), *The Handbook of Measurement: How social scientists generate, modify, and validate indicators and scales*. Thousand Oaks, CA: SAGE Publications.

Bakeman, R., Deckner, D. F., & Quera, V. (2005). Analysis of behavioral streams. In D. M. Teti (Ed.), *Handbook of research methods in developmental science* (pp. 394–420). Oxford, UK: Blackwell Publishers.

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to sequential analysis* (2nd ed.). New York: Cambridge University Press.

Bakeman, R., & Quera, V. (1995). *Analyzing Interaction: Sequential Analysis with SDIS and GSEQ*. New York: Cambridge University Press.

Bakeman, R., & Quera, V. (2008). ActSds and OdfSds: programs for converting INTERACT and the observer data files into SDIS timed-event sequential data files. *Behavior Research Methods, 40*, 869–872.

Bakeman, R., & Quera, V. (2009). GSEQ 5.0 [Computer software and manual]. Retrieved from http://www.gsu.edu/~psyrab/gseq/gseq.html.

Bakeman, R., Quera, V., & Gnisci, A. (2009). Observer agreement for timed-event sequential data: A comparison of time-based and event-based algorithms. *Behavior Research Methods, 41*, 137–147.

Bakeman, R., & Robinson, B. F. (2005). *Understanding statistics in the behavioral sciences*. Mahwah, NJ: Erlbaum.

Blount, R. L., Corbin, S. M., Sturges, J. W., Wolfe, V. V., Prater, J. M., & James, L. D. (1989). The relationship between adults' behavior and children's coping and distress during BMA/LP procedures: A sequential analysis. *Behavior Therapy, 20*, 585–601.

Caldwell-Andrews, A., Blount, R. L., Mayes, L., & Kain, Z. N. (2005). Assessing behavioral interactions in the perioperative environment: Development of the P-CAMPIS. *Anesthesiology, 103*, 1130–1135.

Chorney, J. M., Hammell, C., Blount, R., McLaren, C. E., Chen, W., & Kain, Z. N. (2009). Healthcare provider and parent behavior and children's distress and coping at anesthesia induction. *Anesthesiology, 111*, 1290–1296.

Connor, M., Fletcher, I., & Salmon, P. (2009). The analysis of verbal interaction sequences in dyadic clinical communication: A review of methods. *Patient Education and Counseling, 75*, 169–177.

Durlak, J. (2009). How to select, calculate, and interpret effect sizes. *Journal of Pediatric Psychology, 34*, 917–928.

Gottman, J. M., & Roy, A. K. (1990). *Sequential analysis: A guide for behavioral researchers*. New York: Cambridge University Press.

Haberman, S. J. (1978). *Analysis of qualitative data*. (Vol. 1). New York: Academic Press.

Howe, G. W., Dagne, G., & Brown, C. H. (2005). Multilevel methods for modeling observed sequences of family interaction. *Journal of Family Psychology, 19*, 72–85.

Karazsia, B. T., & van Dulmen, H. M. H. (2008). Regression models for count data: Illustrations using longitudinal predictors of childhood Injury. *Journal of Pediatric Psychology, 33*, 1076–1084.

Roter, D., & Larson, S. (2002). The Roter interaction analysis system(RIAS): Utility and flexibility for analysis of medical interactions. *Patient Education and Counseling, 46*, 243–251.

Stoolmiller, M., & Synder, J. (2006). Modeling heterogeneity in social interaction processes using multilevel survival analysis. *Psychological Methods, 11*, 164–177.

Yoder, P. J., & Tapp, J. (2004). Empirical guidance for time-window sequential analysis of single cases. *Journal of Behavioral Education, 13*, 227–246.